Information, Technology and Information Worker Productivity

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We study the fine-grained relationships among information flows, IT use, and individual information-worker productivity, by analyzing work at a midsize executive recruiting firm. We analyze both project-level and individual-level performance using: (1) direct observation of over 125,000 e-mail messages over a period of 10 months by individual workers (2) detailed accounting data on revenues, compensation, project completion rates, and team membership for over 1300 projects spanning 5 years, and (3) survey data on a matched set of the same workers' IT skills, IT use and information sharing. These detailed data permit us to econometrically evaluate a multistage model of production and interaction activities at the firm, and to analyze the relationships among communications flows, key technologies, work practices, and output. We find that (a) the structure and size of workers' communication networks are highly correlated with their performance; (b) IT use is strongly correlated with productivity but mainly by allowing multitasking rather than by speeding up work; (c) productivity is greatest for small amounts of multitasking but beyond an optimum, multitasking is associated with declining project completion rates and revenue generation; and (d) asynchronous information seeking such as email and database use promotes multitasking while synchronous information seeking over the phone shows a negative correlation. Overall, these data show statistically significant relationships among social networks, technology use, completed projects, and revenues for project-based information workers. Results are consistent with simple production models of queuing and multitasking and these methods can be replicated in other settings, suggesting new frontiers for bridging the research on social networks and IT value.

Key words: Social Networks, Productivity, Information Worker, IT, Multitasking, Production Function

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"In the physical sciences, when errors of measurement and other noise are found to be of the same order of magnitude as the phenomena under study, the response is not to try to squeeze more information out of the data by statistical means; it is instead to find techniques for observing the phenomena at a higher level of resolution. The corresponding strategy for [social science] is obvious: to secure new kinds of data at the micro level." -- *Herbert Simon*

1. Introduction

Information workers now account for as much as 70% of the U.S. labor force and contribute over 60% of the total value added in the U.S. economy (Apte & Nath 2004). Ironically, as more and more workers focus on processing information, researchers have less and less information about how these workers create value. Unlike bushels of wheat or tons of steel, the inputs and real output of most information workers is difficult to measure. Yet, as the information content of work increases, the role of information flows in information intensive work becomes increasingly central to our understanding of the performance of individuals, groups and organizations.

Efficient access to useful information should promote information worker productivity by facilitating faster, higher quality decision making. If information access influences productivity, its distribution and diffusion patterns should in turn correlate with the relative productivity of information workers. In the information age, new technologies, new ways of working, and an increasing availability of information could significantly affect productivity and specifically the productivity of information workers. Studies of IT-productivity demonstrate a strong positive relationship across distinct measures (Bharadwaj et. al. 1999, Brynjolfsson & Hitt 2000, Aral & Weill 2007) at the country (e.g. Dewan & Kraemer 2000), industry (e.g. Jorgenson & Stiroh 2000), and firm (e.g. Brynjolfsson & Hitt 1996) levels. Yet, we lack a micro-level understanding of how IT and information influence productivity. While a handful of micro-level studies of IT and productivity have been conducted in recent years (e.g. Ichniowski, Shaw & Pernushi 1997, Barua, Kreibel & Mukhopadhyay 1994, Mukhopadhyay, Surendra & Srinivasan 1997, McAfee 2002), most focus on manufacturing industries and measure physical goods output, leaving a number of important questions unanswered. The mechanisms by which IT and information affect productivity are not well understood and the output and production functions for information workers such as managers, consultants, researchers, marketers, lawyers and accountants remain poorly modeled and measured. Ironically, IT may be especially important for the productivity of information workers because it enables them to search for, retrieve, analyze and store information (a key input into their decisions and activities), and enables new forms of work organization and communication that are increasingly asynchronous, geographically dispersed and sustained over longer periods of the day (Hinds & Kiesler 2002).

Information workers gain access to information through both social and technological means. Accordingly, we bridge two literatures – social networks and IT value – to understand how social and technological access to information correlates with information worker productivity. We explore a new frontier for IT productivity research by opening the black box of the firm using detailed project-level data at the level of individual information workers to shed light on the intermediate mechanisms that explain performance. By studying a single industry in depth, Ichniowski, Shaw and Prennushi (1997) were able to specify a production function for blue collar workers, and then to measure the effects of particular technologies and work practices on productivity. We undertake an analogous strategy for comprehending information work: secure individual and project-level data for information workers and map their behaviors to project output. We focus on executive recruiters, or "head hunters," whose project output is precisely measurable. Accounting records provide detailed data on individual and project-level revenues, the number of projects individuals and teams complete, precise start and stop dates, the number of concurrent projects, and individual share-weighted effort. With company and employee cooperation, we also monitored email usage to analyze the flow of information through the firm's social network, conducted field interviews, gathered survey data, and collected independent third party evidence of project difficulty. This micro data allows us to match individual level behaviors to individual and project level results.

Our variables measure the *use* of IT, not merely its presence, and include direct, message-level observation of communications volume, the size and structure of email contact networks, professed ability to use database technology, and relative time spent on various information seeking tasks. When combined with interviews and visits, these data enabled us to specify and estimate several equations relating social network structure, technology, skill, worker characteristics, task completion and revenue generation. Narrowly focusing on one industry allowed us to precisely define the white collar production process, and our concentrated data collection from one firm eliminates many sources of heterogeneity that confound productivity estimation at more aggregate levels of analysis.

Our results demonstrate that information flows and IT use do in fact predict significantly higher levels of economic productivity. Richer communications structure predicts greater multitasking and productivity, and heavier database users generate more revenue for the firm per unit time. However, our analyses at the project level, designed to unpack the processes driving performance, also reveal some counterintuitive results. We find that individuals occupying central brokerage positions in the firm's communication network, who arguably have more structurally efficient access to novel information, are not necessarily more efficient *per project*. Instead, their higher levels of productivity result from higher capacities to multitask across simultaneous projects. Employees who use databases more also conduct more work simultaneously and finish projects faster, demonstrating that technology use not only speeds work, it enables new ways of working that can make workers more productive. Together, our results reveal a substantial program of correspondence among information, technology and output, and motivate new questions regarding the tradeoffs between multitasking and the speed of work, and how information affects intermediate production processes in white collar work.

2. Theory and Literature

2.1. Information Flows, Social Network Structure and Information Worker Productivity

Access to information should promote information worker productivity by (a) supporting higher quality decisions, (b) facilitating the development of managerial skills and (c) enabling more effective political maneuverability. Information and reductions in uncertainty improve resource allocations and decision making and reduce delay costs by increasing the accuracy of mental mappings from actions to expected consequences (Cyert & March 1963, Marschak & Radner 1972, Galbraith 1973). Our context aligns well with the classic decision-theoretic interpretation of the value of information: improved information about the executive candidate pool and about job opportunities improves the fit between candidates and clients' requirements, increasing the frequency of matches and reducing time wasted interviewing unsuitable candidates. Precise information also tempers risk aversion, enabling recruiters to make appropriate decisions faster (Arrow 1962, Stiglitz 2000). Reductions in uncertainty help recruiters place the right candidates in front of the right clients quickly, increasing the likelihood of concluding searches faster and in turn increasing the job completion rate and the revenues earned by the firm. Sharing procedural information or know-how can also improve employees' handling of recurrent search problems (Szulanski 1996) and recruiters report learning to deal with difficult professional situations through peer communication.

Access to information also enables skill development by increasing familiarity and facility with different topics, improving individuals' absorptive capacity and strengthening communication. As people are exposed to new ideas and information they develop the ability to absorb new concepts enabling more effective knowledge transfer (Cohen & Levinthal 1990, Simon 1991) and increasing the likelihood that others will share information with them as they share more intellectual common ground (Clark 1996, Cramton 2001, Reagans & McEvily 2003). As absorptive capacity is developed, individuals are better able to communicate ideas across a broader range of topics and to a broader audience, strengthening persuasion and the ability to generate support from subject matter experts in accomplishing managerial goals (Rodan & Galunic 2004). Access to information can also create autonomy (Simmel 1922 (1955), Burgelman 1991, Burt 1992) and enable political maneuverability (Padgett & Ansell 1993), helping individuals gain access to resources they need to do their jobs efficiently (Rodan & Galunic 2004).

In our setting, employees seek and access information socially through colleagues and contacts, and technologically by searching databases, intranets and public information available online. The structure of social information acquisition is instantiated in communication networks that connect employees. Two of the most important network characteristics theorized to drive performance by providing access to information are structural diversity (the existence of 'structural holes' in a communication network, Burt 1992) and short path lengths to different parts of the network (high 'betweenness centrality'; e.g. Freeman 1979, Hansen 2002). While social network research has studied these concepts through survey based self reports, none has linked information flowing in email networks to productivity – an important lens onto how information flows affect the performance of information workers.[1]

Actors with structurally diverse social networks (networks rich in structural holes that link them to unconnected network neighborhoods) derive 'information benefits' from network structure because they are more likely to receive non-redundant information through network contacts (Burt 1992). As information in local network neighborhoods tends to be redundant, structurally diverse contacts provide

[1] A handful of recent papers examine email networks (e.g. Wu et. al. 2004, Kossinets & Watts 2006), but do not address these structural characteristics or productivity and performance.

channels through which novel information flows to individuals from distinct pools of social activity (Granovetter 1973). Access to non-redundant information facilitates early promotion (Burt 1992), greater career mobility (Podolny & Baron 1997), adaptation to change (Gargiulo & Benassi 2000), and R&D productivity (Reagans & Zuckerman 2001). In social networks, the economic value of information stems from its uneven distribution across actors. Individuals solve problems and find opportunities by tapping distinct information pools in diverse network neighborhoods to which their structurally diverse channels provide access. Actors with access to these diverse pools "benefit from disparities in the level and value of particular knowledge held by different groups…" (Hargadon & Sutton 1997: 717). Redundant information is less valuable because many actors are aware of it at the same time, reducing opportunities associated with its use. Structural redundancy is also inefficient because actors incur costs to maintaining redundant contacts while receiving no new information from them (Burt 1992). Qualitative studies show that executive recruiters fill "brokerage positions" between clients and candidates and rely heavily on non-redundant information flows to complete their work effectively (Finlay & Coverdill 2000). Recruiting teams with novel information about newly available candidates or positions can fill diverse client requirements more quickly and accurately. We therefore expect that *individuals and teams with unconstrained (or diverse) communication networks are more productive.* (Hypothesis 1a)

While network diversity provides novel information from different local network neighborhoods, being along the shortest network paths to the greatest number of potential contacts may also increase access to information. Business units with shorter path lengths to other units, those with high betweenness centrality (Freeman 1979), finish projects faster (Hansen 2002). There are two broad information search benefits to higher betweenness centrality. First, longer path lengths increase the likelihood and severity of distortion as information is passed from individual to individual in a network (March & Simon 1958, Huber 1982, Hansen 2002). When information about the candidate pool or impending layoffs at a source firm are passed from recruiter to recruiter, there are an increasing number of chances for misunderstanding, vagueness, filtering or even deliberate withholding and falsification (Huber & Daft 1987). The potential for garbling increases in proportion to the social distance traversed by messages, in this case the number of people along the message path. A common anecdotal example of this phenomenon is the telephone game, in which messages become distorted as they are passed along a chain of contacts. Second, when information is vague or imprecise teams must take time to verify its accuracy and relevance, and obtain complementary information to enable effective decision making (Hansen 2002). For example, when a recruiter receives second hand information about a potential candidate, they must verify the candidate's prior experience and leadership potential in order to qualify them as a possible match for a given position. In contrast, short path lengths provide direct information with less distortion, and reduce search costs associated with verification. Recruiters can request clarification directly from the message source rather than wasting time tracking down the source or establishing where the information was garbled. Without knowing the origins of distortions, teams may search for extended periods of time and in a costly manner to collect and verify the information they need to make high quality decisions. We therefore expect that *individuals and teams located on the shortest path lengths to other individuals in the firms' communication network are more productive*. (Hypothesis 1b)

2.2. IT Use, IT Skills and Information Worker Productivity

Information workers also gather, process and analyze information by technological means. Information contained in databases, document repositories and Intranets are frequently used to conduct due diligence and aid decision making. In our context recruiters use the Executive Search System (ESS) and external proprietary databases to conduct research essential to their information processing and decision making tasks. These systems also provide decision support with value added information sorting, extraction and summarization tools that enable more efficient and effective search and analysis. A well established literature in Information Systems examines the antecedents of IT acceptance and use in organizations (e.g. Davis 1989, Straub et. al. 1995, Szajna 1996, Taylor & Todd 1995, Doll and Torkzadeh 1998, Venkatesh & Davis 2000), and a handful of studies advocate systems use as the "missing link" between IT investments and performance improvements (e.g. Lucas & Spitler 1999, Devaraj & Kohli 2003). These studies argue that "[s]ystems-use is a pivotal construct in the system-to-value chain," (Doll and Torkzadeh 1998) implying that differences in IT use are correlated with productivity, performance and value creation. Goodhue & Thompson (1995) contend that this link is especially pronounced in contexts where the technology (its design and function) "fits" employees' task requirements well. We examine the use of the Executive Search System (ESS) and external proprietary databases, both of which are designed specifically to support recruiters' information seeking and decision making needs. We therefore expect that: *Individuals and teams who use the ESS and external proprietary databases more are more productive.* (Hypothesis 2a)

Task-technology fit depends not only on the match between technology and its application, but also on the skills of the individuals using the technology (Goodhue & Thompson 1995). A strong empirical relationship between IT use and skill at the worker (Kreuger 1993), firm (Dunne, Haltiwanger & Troske 1997), and industry (Autor, Katz & Kreuger 1998) levels, demonstrates that firms with significant amounts of IT capital tend to hire more skilled workers. A handful of firm level studies also demonstrate that the co-presence of IT and highly skilled labor improves productivity and performance (Breshnahan, Brynjolfsson & Hitt 2002, Aral & Weill 2007). Although most individual level studies of the impact of IT use on productivity and performance do not evaluate the relative IT skills of workers (e.g. Lucas & Spitler 1999, Devaraj & Kohli 2003), there are good reasons to believe that IT skills and IT use should be correlated and that stronger IT skills should contribute to the productivity of information workers. Information intensive work is generally supported by "data analysis skills" which complement IT to improve productivity (Bresnahan, Brynjolfsson & Hitt 2002) and firms whose employees have stronger IT skills perform better on average (Aral & Weill 2007). We therefore expect that: *Individuals and teams with stronger IT skills are more productive.* (Hypothesis 2b)

2.3. Intermediate Mechanisms: Multitasking & the Speed of Work

Recruiters earn revenue by filling client positions rather than billing hourly and real output is therefore generated by completing projects. As recruiters complete more projects per unit time, they generate more real output per unit time. If we consider recruiters to be managing queued projects, the faster they complete each project and take on more work the more projects they will complete and the more real output they will produce per unit time. We therefore expect that: *Workers who finish projects faster are more productive as measured by overall project completion rate and revenue generation.* (Hypothesis 3)

Project-level multitasking – the act of taking on multiple simultaneous projects in parallel – allows recruiters to accomplish more work by utilizing lulls in one project to accomplish tasks related to other projects. As is typical in project based work, there are periods of downtime during projects when recruiters wait to have phone calls returned or interviews scheduled. The non-continuous nature of project based work is naturally suited to parallel processing across multiple simultaneous projects. Multitasking creates efficiency in information worker production by smoothing labor hours over projects with bursty work requirements. We therefore expect that: *Workers who take on more simultaneous projects are more productive as measured by overall project completion rate and revenue generation.* (Hypothesis 4a)

However, taking on multiple simultaneous projects is costly. As more projects are attempted in parallel, recruiters face longer delays in getting back to the activities of a particular project while cycling through activities related to other projects. These delays may preclude timeliness or force recruiters to skip lower priority activities that could help fill positions. When employees juggle too many projects, work gets backed up and productivity suffers. The situation is analogous to congestion and throughput processes for queued tasks. For example, the throughput of cars on a highway increases as more cars join traffic, but is reduced by congestion after a certain level of traffic is exceeded. Multitasking is associated with short-term and long-term cognitive switching costs that reduce reaction times and task completion rates, and increase error rates in experimental settings (e.g. Rubenstein et. al. 2001). Overlapping activities create confusion and associative competition, and responses are substantially slower and more error-prone with frequent task switching (Gilbert & Shallice 2002, Monsell 2003). Our interviews corroborate this story. As the CIO of the firm put it "Everyone can only deal with so many balls in the air. When someone gets 'too far in,' [takes on too many projects] they lose touch. They can't tell one project from another." If this is the case, then a fundamental trade-off is likely to exist between workload and efficiency, such that multitasking beyond a certain point reduces productivity. We therefore expect that:

There are diminishing marginal productivity returns to project based multitasking and that multitasking beyond an optimal level reduces productivity. (Hypothesis 4b)

Network position and IT use and skill should in turn correlate with multitasking and the speed of work. Multitasking allows recruiters to smooth labor hours over projects with bursty work requirements. Periods of downtime during projects create interstitial spaces during which work on other projects can be accomplished. Asynchronous communication and information seeking technologies should complement the efficient use of these project lulls by allowing recruiters to seek information and expertise without the constraints of coordinating the availability of information sources. We therefore hypothesize that: *The use of asynchronous communication and information seeking technologies – Email and Database – is positively associated with multitasking, while the use of synchronous communications methods – Phone and Face-to-Face communication – is negatively associated with multitasking.* (Hypothesis 5a)

Favorable network positions (e.g. unconstrained networks with high betweenness) enable more effective social information gathering by increasing access to non-redundant information and reducing garbling, noise and costly verification and search behaviors. Recruiters who are well positioned to gather information are likely to make better decisions during the search process and to conclude searches more quickly. In other work which analyzes the content of the email data, we find that recruiters with greater access to novel information and those employees who are more likely to receive diffusion of news and information in email and to receive such information sooner than others in the firm's network are indeed more productive (Aral, Brynjolfsson & Van Alstyne 2007, Aral & Van Alstyne 2007). We therefore expect that: *Individuals and teams with unconstrained communication networks finish projects faster* (Hypothesis 6a), and that: *Individuals and teams located on the shortest path lengths to other individuals in the firms' communication network finish projects faster.* (Hypothesis 6b)

3. The Research Setting and the Role of Information and Technology

We studied a medium-sized executive recruiting firm over five years, with fourteen regional offices throughout the United States. The employees occupy three basic positions – partner, consultant and researcher – and conduct their 'executive searches' in teams. Our interviews indicate that the contract execution process is relatively standard: A partner secures a contract with a client and assembles a project team (team size mean = 1.9, min = 1, max = 5). The team then establishes a universe of potential candidates including those in similar positions at other firms and those drawn from the firm's internal database. These candidates are vetted on the basis of perceived quality, their match with the job description and other factors. After conducting initial due diligence, the team chooses a subset of candidates for internal interviews, approximately six of whom are forwarded to the client along with a formal report of the team's due diligence. The team then facilitates the client's interviews with each candidate, and the client, if satisfied with the pool, makes offers to one or more candidates. A contract is considered complete when a candidate accepts an offer. The period from client signature to candidate signature defines project duration.

The core of executive recruiters' work involves retrieving and understanding clients' requirements and matching candidates to those requirements.[2] This matching process is information-intensive and requires assembling, analyzing, and making decisions based on information gathered from various sources including team members, other firm employees, contacts outside the firm, and data on potential candidates in the internal proprietary database, external proprietary databases, and public sources of information. Recruiters earn revenue by filling vacancies, rather than billing hourly. The speed with which vacancies are filled is therefore an important intermediate measure of productivity. Contract completion implies that the search team has met the client's minimum thresholds of candidate fit and quality, and given controls for differences across contracts (e.g. job type, location), project duration (in addition to real dollar output value) can be interpreted as a quality controlled measure of team and worker productivity.

Interviews with the CIO and other employees indicate that the firm uses IT in essentially two ways: 1) as a communication vehicle (e.g. phone, voicemail, and email) and 2) as a central repository of information and knowledge about ongoing projects, potential candidates and internal task coordination. Both of these functions facilitate the information exchanges teams require to systematically assemble,

[2] "Client" refers to a firm seeking to hire one or more executives; "candidate" refers to a potential hire; and "recruiter" refers to someone expert in locating, vetting, and placing candidates.

analyze, codify and share knowledge about candidates and clients. The firm pays to use external databases and has its own proprietary Executive Search System (ESS), built from an off-the-shelf relational database. The ESS provides a repository of information on current and past projects, the firm's own employees (e.g. contact information, areas of expertise, work history and current assignments), clients, and potential candidates (e.g. resumes, prior due diligence, and notes or "work ups" on their previous jobs); and also helps employees coordinate and manage dependencies across projects. For example, when searching for potential candidates, employees must honor contractual obligations that prevent them from poaching employees of previous clients for one year. The ESS maintains an up-to-date record of candidates that are 'frozen' due to prior client obligations and employees use this information to coordinate contractual obligations across projects and to reduce time spent interviewing ineligible candidates.

4. Model Specification

4.1. A Production Model of Revenue and Project Output for Executive Recruiting

A decade ago, moving from aggregate data to more fine grained data at the firm level helped resolve the 'IT productivity paradox.' Explorations at the firm level, however, are still constrained by the granularity of the data and can only explain *whether* IT increases productivity, not *how* IT increases productivity. Our data allow us to construct a detailed model of the production process of executive recruiters, and to test the impact of IT and information flows on intermediate process metrics and final output measures. We conduct both individual-level and project-level analyses that examine the specific mechanisms through which IT and information affect the production process.

We apply a traditional microeconomic production function framework to the production process of information workers in which employees use information based inputs to produce information based products and services. Like much of the work that estimates the productivity effects of IT capital (e.g. Hitt & Brynjolfsson 1995, Brynjolfsson & Hitt 1996, Dewan & Min 1997, Jorgenson & Stiroh 2000), we begin with a generalized production function describing output (Q) as a function of ordinary capital (K), computer capital (C) and labor (L):

$$Q_{it} = f_1(C_{it}, K_{it}, L_{it}). \tag{1}$$

The Cobb Douglas production function is the most common and widely validated functional form used to estimate the productivity effects of IT capital at the firm level. It has the appealing property that the coefficients can be directly interpreted as output elasticities (Hitt & Brynjolfsson 1995):

$$Q_{it} = C_{it}^{\beta_1} K_{it}^{\beta_2} L_{it}^{\beta_3}. \tag{2}$$

By taking logarithms and adding an error term, this function produces a reduced form equation that can be estimated using firm level data where β_1, β_2 and β_3 are parameters to be estimated:

$$\log Q_{it} = \alpha_{it} + \beta_1 \log C_{it} + \beta_2 \log K_{it} + \beta_3 \log L_{it} + \varepsilon_{it}. \tag{3}$$

We adapt this framework to reflect the production function of individual information workers in the context of executive recruiting by modifying both the unit of analysis and the definition of inputs.

Since recruiters generate revenue by completing projects (rather than billing hourly) and are assigned to projects with varying levels of individual effort share per project, we define real output (*Q*) as the revenues generated by each recruiter and conceptualize completed projects (*P*) as the primary driver of revenues such that $Q_{it} = f_2(P_{it})$. Individual workers use the accumulated capital of the firm to execute tasks. Investments in ordinary capital (*K*) (e.g. property and equipment, buildings, offices, desks and meeting rooms) and IT capital (*C*) (e.g. personal computers, phones, fax machines, copiers and projectors) are uniform across workers in that employees have equal access to them. We therefore conceptualize ordinary capital (*K*) and IT capital (*C*) as constant across employees and embodied in the constant term of the production function (α). Instead of measuring IT capital, our input variables focus on access to information and technology use. We include two new categories of inputs to the production function based on our hypotheses: IT use and skills (*IT*) and communication network structure (*NS*) (a proxy for access to information inputs).[3] The move away from measuring ordinary capital and computer capital to measuring IT use and skills and social network structure allows us to precisely estimate relationships among IT

[3] We include a series of control variables to account for traditional demographic and human capital variables (e.g. age, gender, level of education, industry experience and managerial level), job type, temporal variation and city characteristics.

use, information access through social networks and output in information work settings using the reduced form equation expressed in equation [4].

$$Q_{it} = f_2(P_{it}) = f_3(IT_{it}, NS_{it}) = \alpha_{it} + \beta_1 IT_{it} + \beta_2 NS_{it} + controls + \varepsilon_{it} \qquad [4]$$

However, this reduced form has two limitations. First, it may produce noisy measures of the relationships because several intermediate process steps separate using IT and accessing information from producing real output. Second, while these estimates uncover whether IT use and information access through social networks are associated with output, they cannot tell us how these factors are related. We therefore developed our model further, using interviews and site visits as a guide, to sharpen our estimates and to examine how IT is related to output through intermediate process mechanisms.

The labor term (*L*) in firm-level production functions typically describes the number of employees or the wage adjusted cost of labor inputs. In white collar work settings, where workers do not bill hourly and in which labor is not compensated by the hour (as in our case), employees are given autonomy to choose when and how they work, rather than fulfilling a certain quota of hours worked per week. If we consider white collar workers to be managing queued tasks, each with distinct start and stop points, we can measure the relationship between IT, information flows, and intermediate measures of output. In particular, data on project multitasking and start and stop times over the sample period index the rate at which projects are completed. In our production model, employees work on projects whose number and duration determine total dollar "bookings" (contracts landed) and "billings" (contracts executed) revenue. The production function therefore characterizes output as a multiplicative function of the number of simultaneous projects (MT_{it}) and project duration (D_{it}), as specified in equations [5] and [6].

$$Q_{it} = f_1(P_{it}) = f_2(MT_{it}, D_{it}) = MT_{it}^{\beta_1} * D_{it}^{\beta_2} \qquad [5]$$

$$\log(Q_{it}) = f_1(P_{it}) = \alpha + \beta_1 \log(MT_{it}) + \beta_2 \log(D_{it}) + controls + \varepsilon_{it} \qquad [6]$$

These specifications are derived from models of queued task execution in services work (e.g. Adler et. al. 1995, Hopp et. al. 2007) and from models of parallel and overlapping queued task processing (e.g. Krishnan et. al. 1997) from the engineering and operations management literatures, which specify the execution of queued tasks as a multiplicative function of load (e.g. multitasking) and speed (e.g. duration).

Finally, we relate IT use and skills and network structure to the intermediate mechanisms that describe the production process. We relate the hypothesized inputs to multitasking through the following linear additive specification which resembles those of Ichniowski, Shaw & Prennushi (1997). Increment to R^2, PE and Box-Cox tests indicate this additive form is preferred to a multiplicative Cobb-Douglas specification in equations [7] and [8]:

$$MT_{it} = f_3(IT_{it}, NS_{it}) = \alpha_{it} + \beta_1 IT_{it} + \beta_2 NS_{it} + controls + \varepsilon_{it} . \qquad [7]$$

To test whether IT, information flows and the level of multitasking are related to project duration (*D*), we develop a parsimonious model of project completion rate $R(t)$. As the dataset contains right censored data,[4] OLS estimation can produce biased and inconsistent results of rate analyses (Tuma & Hannan 1984). We therefore use a hazard rate model of the likelihood of a project completing on a given day, conditional on it not having been completed earlier. We employ the Cox proportional hazards model in equation [8] to estimate relationships among IT use, information flows and the completion rate:

$$R(t) = r(t)^b \exp[\alpha_{it} + \beta_1 IT_{it} + \beta_2 NS_{it} + \beta_3 MT_{it} + controls + \varepsilon_{it}], \qquad [8]$$

where $R(t)$ represents the project completion rate, t is project time in the risk set, and $r(t)^b$ the baseline completion rate. The effects of independent variables are specified in the exponential power. The coefficients in this model have a straightforward interpretation: β_i represents the percent increase or decrease in the project completion rate associated with a one unit increase in independent variable *i*.[5] Coefficients greater than 1 represent an increase in the project completion rate (equal to β_i - 1); coefficients less than 1 represent a decrease (equal to 1-β_i). Our aggregate model of production activity is therefore expressed using equations [6], [7] and [8] in concert. The relationships are depicted graphically in Figure 1.

[4] This reflects projects that did not complete during the observation window.

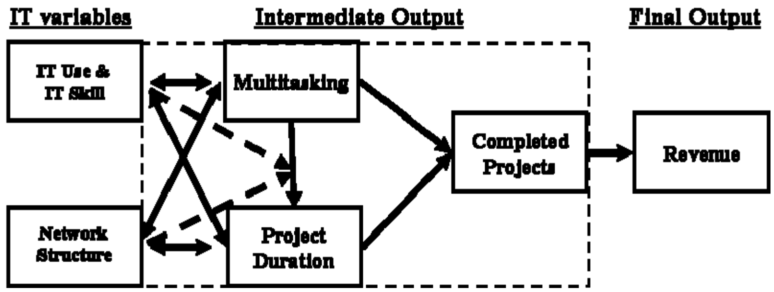

Figure 1. Our model of the production function represents a set of queued job tasks. The influence of IT and Information Flows can then be examined at the individual and project levels.

5. Data & Measurement

5.1. Data

Data for this study include three data sets from inside the firm and one from outside the firm. The first is complete accounting records of: (i) revenues generated by individual recruiters, (ii) contract start and stop dates, (iii) projects handled simultaneously, (iv) project team composition and share weighted effort, (v) job levels of recruiters, and (vi) job levels of placed candidates. Accounting data cover the period 2001-2005. These provide excellent output measures that can be normalized for quality.

The second data set covers 10 months of complete email history captured from the corporate mail server during two equal periods from October 1, 2002 to March 1, 2003, and from October 1, 2003 to March 1, 2004. Email data has the potential to overcome bias in survey respondent recall of their social networks (e.g. Bernard et. al 1981) by objectively recording who communicates with whom and when. However, email is not without its own limitations. We therefore took great care in collecting and analyzing our social network data. We designed and developed capture software specific to this project and took multiple steps to ensure data integrity and boost participation while minimizing bias, intrusiveness, and risks to security. We used cryptographic techniques to preserve individual privacy and excluded spam messages by eliminating external contacts who did not receive at least one message from someone inside the firm. The project went through nine months of human subjects review prior to launch. Details are provided in Appendix A and in Van Alstyne & Zhang (2003). Participants received $100 in exchange for

[5] Specification tests reveal no significant duration dependence in our explanatory variables, and the proportional hazards assumption is shown to be valid using both statistical and graphical tests.

permitting use of their data resulting in 87% coverage of eligible recruiters and more than 125,000 email messages captured.[6]

The third data set contains survey responses on information-seeking behaviors, experience, education, human factors, and time allocation. Survey questions were generated from a review of relevant social network, behavioral and economic literature and more than two dozen interviews with recruiters. Survey methods and the questions themselves are presented in Appendix B. Experts in survey methods at the Inter-University Consortium for Political and Social Science Research vetted the survey instrument, which was pre-tested for comprehension and ease-of-use. Participants received $25 for completed surveys and participation exceeded 85%.

The fourth data set, gathered outside the firm, involves independent controls for placement city attributes used to control for project difficulty and described in Section 5.2 below. Together, these data provide a desktop-level view of information flows and IT use that we matched to precise measures of individual performance.

5.2. Independent Variable Construction

Social Network Structure. To measure information flows we constructed variables for both the amount of email sent and received and the network structure of email traffic at both the individual and team levels. Since teams at our research site are small (two recruiters per team on average) we focus on the global network structure of teams' external contacts, rather than their internal structure which is typically dyadic. Measures of the level of email traffic count the *total number of emails sent and received*, *network size* (the number of contacts), and *in-degree* and *out-degree centrality*, which measure the message frequency weighted number of contacts.[7] We also measure the two aspects of network structure hypothesized to influence information access: betweenness centrality and network diversity.

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[6] *F*-tests comparing performance levels of those who opted out with those who remained did not show statistically significant differences. *F* (Sig): Revenue02 2.295 (.136), Compensation02 .837 (.365), Multitasking02 .386 (.538).

[7] We distinguish between incoming and outgoing email to proxy for differences between information seeking and information provision and, in order to control for the overall level of communication, control for the total amount of email in our analyses.

Betweenness Centrality. The betweenness centrality of an individual's email network $B(n_i)$ (Freeman 1979),[8] measures the probability that the individual will fall on the shortest path between any two other individuals linked by email communication. We examine degree and betweenness centrality measures as proxies for the likelihood of being privy to useful information.

$$B(n_i) = \sum_{j<k} g_{jk}(n_i) \Big/ g_{jk} \qquad [9]$$

Network Diversity. The '*constraint*' of the network C_i (Burt 1992: 55)[9] measures the degree to which an individual's contacts are connected to each other (a proxy for the redundancy of contacts):

$$C_i = \sum_j \left(p_{ij} + \sum_q p_{iq} p_{qj} \right)^2, \quad q \neq i, j. \qquad [10]$$

Network constraint measures the lack of structural holes in the network, and we measure *network diversity* (the presence of structural holes) as 1 - C_i – a measure of the efficiency with which recruiters can access non-redundant information. Two four week patterns of email traffic are shown in Figure 2.

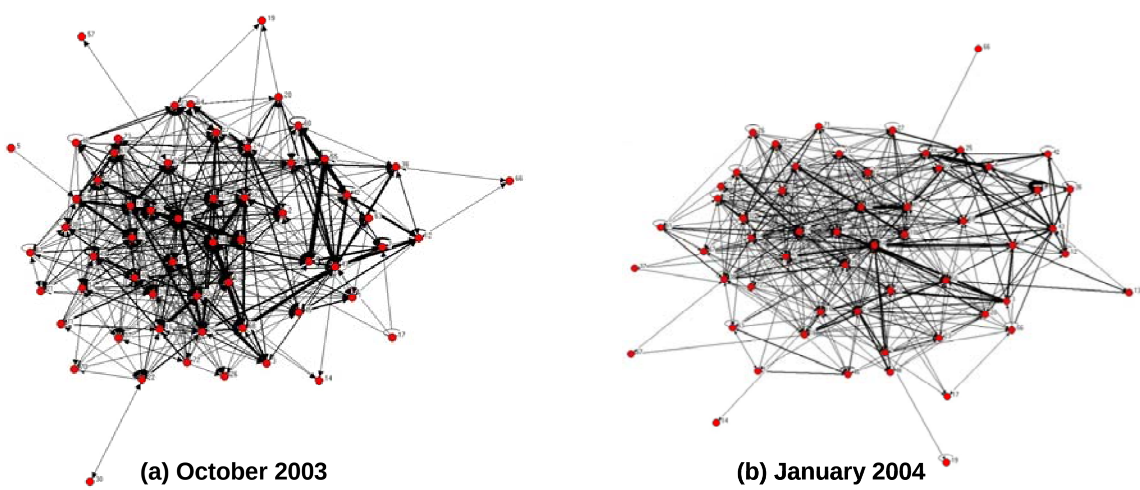

Figure 2. We use email messages to map the social network at this firm. Each node represents an individual in our data set, while the thicknesses of the links represent the amount of email traffic.

IT Use & IT Skill. Following our qualitative assessment of the role of IT in the firm's production process, we concentrated our measurement of IT around (a) the intensity and skill with which employees

[8] Where g_{jk} is the number of geodesic paths linking *j* and *k* and $g_{jk}(n_i)$ is the number of geodesic paths linking *j* and *k* involving *i*.

[9] Where $p_{ij} + \sum p_{iq}p_{qj}$ measures the proportion of *i*'s network contacts that directly or indirectly involve *j* and C_i sums this across all of *i*'s contacts.

used the ESS system and external proprietary databases, and (b) the frequency of use of different modes of communication in maintaining contacts and seeking information. In measuring ESS skill, we asked respondents to evaluate (i) their personal effectiveness using the ESS system and (ii) their ability to find, add, and modify the records it contains. As these two factors were highly correlated (Spearman = .88***, $\alpha = .94$), we combined them into a single measure. To measure ESS use intensity, we asked respondents to estimate the proportion of time they spent gathering information from the ESS and external databases to perform their work. Finally, we asked respondents to estimate the number of people they communicated with in a typical day face-to-face, over the phone, and over email.[10]

Multitasking. Research in laboratory settings has examined task execution time and error rates for simple object classification or arithmetic tasks with visual task cue interruptions (e.g. Rubenstein et. al. 2001). In the context of information work, we hypothesize that employee work load (the number of simultaneous projects engaged in per unit time) is likely correlated with IT use and output. We therefore define project-level multitasking as the act of taking on multiple simultaneous projects in parallel. We measure individual multitasking (MP_i) by the effort share weighted number of projects an employee is working on during any given day $MT_{it} = \sum_p \omega_{pi}$, where $0 \le \omega_{pi} \le 1$ is *i*'s effort on project *p*.[11] We measure team multitasking (MT_p) as the average number of projects a team is working on between the start and stop dates of a given focal project, again weighted by assigned effort shares: $MT_{pt} = \frac{\sum_i MT_{it}}{i}$.

5.3. Control Variables

Characteristics of Individual Recruiters. We included controls for traditional demographic and human capital variables (e.g. age, gender, level of education, industry experience and managerial level) to

[10] As we also have an objective measure of this value, we assessed the accuracy of survey responses. Respondents reported a mean number of email contacts equal to 28.1, while the email data revealed a mean of 34.8 (Individual mean email contacts = 28.1, team mean = 20.1). We could not reject the hypothesis that the difference between these means was zero at the 95% level.

[11] ω_p is precisely recorded in the firm's accounting data as a percent share of the project.

control for observable differences in worker education, skill and experience. We also utilize fixed and random effects specifications to control for unobserved heterogeneity across individual recruiters.

Project Characteristics. Certain positions may be easier or harder to fill. Clients may demand that new CEOs be named quickly. Senior executives also have more experience with recruiters and with job mobility. To control for the effect of *Job Type*, we include a dummy variable for the eight job classes the firm recognizes in its own records.[12] We also control for *Task Characteristics*, measured by survey responses about the routineness and interdependence of tasks for similar reasons. Adding more labor to a project may speed work or slow it down depending on tradeoffs between the complexity of a larger team and the output contribution of additional labor. We therefore include a variable measuring *Team Size*.

City Characteristics. Crime rates, weather conditions, the cost of living and other city characteristics may affect the attractiveness of a position and influence contract completion due to placement difficulty. To control for these factors we collected data on the 768 cities in our sample from the web site Sperling's Best Places.[13] Factor analysis revealed four underlying factors with significance in our models: *cost of living*, *crime rates* (violent and property crime per capita), *weather conditions* (sunny days per annum) and *commute time*. We therefore included these controls in project-level analyses.[14]

Temporal Variation. In our data business exhibits seasonal variation, picking up sharply in January and declining steadily throughout the year. Exogenous shocks to demand for executive recruiting services could drive increases in both the amount of work employees take on (multitasking) and the revenues they generate. In this case, we could find a spurious correlation between multitasking and revenues driven by an exogenous pulse in demand for the firms' services. There may also be non-seasonal transitory demand shocks in a given year or month of a year. We control for both seasonal and transitory variation in

[12] The firm categorizes jobs by the categories: CEO, COO, CIO, Medical Executive, Human Resources Executive, Business Development Executive and 'Other.' We also ran specifications controlling for sub-categories of 'Other' jobs clustered by their project descriptions, which returned similar results. We therefore retain the firm's original classification.

[13] http://www.bestplaces.net/

[14] We collected city level data on *tax rates for sales, income and property, the aggregate cost of living, home ownership costs, rate of home appreciation, air quality, water quality, number of superfund sites near the city, physicians per capita, health care costs per capita, violent and property crime per capita, public education expenditures per capita, average student to teacher ratio, an index of ultraviolet radiation levels, risk indices for earthquakes, tornadoes and hurricanes, average number of sunny, cloudy, and rainy days per year, average number of days below freezing per year* and *average commute time to work.*

our data with dummy variables for *year, month* and *year/month* separately. Tables 1 and 2 provide variable descriptive statistics and Appendix C provides their descriptions and data sources.

Table 1: Project Level Descriptive Statistics

Variable	Obs.	Mean	SD	Min	Max
Project Team Variables					
Team Size	1382	1.98	.60	1	5
Age	1372	45.07	7.77	27	63
Education	1372	17.74	1.02	15	20
Industry Experience	1372	14.47	7.94	1	39
Multitasking	1382	8.86	2.84	1.60	18.31
Project Duration (Days)	1382	206.90	123.69	3	981
Project Revenue Value ($)	1301	56962.5	25780.7	11666	237636
Team Interdependence	1382	1.36	.749	.05	4.65
Task Routiness	1382	1.18	.88	.05	4
F2F Contacts	1382	4.20	8.68	0	75
Phone Contacts	1382	15.76	10.54	1	70
Email Contacts	1382	20.14	18.46	1	100
ESS (Database) Skill	1382	3.10	1.92	.12	9.30
ESS (Database) Use (%)	1382	15.79	14.45	0	80
Total Emails	1382	1365.67	760.19	.6	3939
Total Emails Sent	1382	667.89	393.96	.3	1985
Total Emails Received	1382	697.79	378.34	.3	1954
Degree Centrality	1382	1295.23	720.24	.6	3584
In Degree	1382	632.66	373.01	.3	1804.2
Out Degree	1382	662.56	360.04	.3	1854
Network Size	1382	37.80	11.90	.6	79.36
Betweenness Centrality	1382	37.55	26.12	0	185.69
Network Diversity (1-Constraint)	1382	.81	.07	.51	.98
City Characteristics					
Cost of Living	1187	358.65	144.49	233.60	2059.60
Crime per Capita	1187	6262.40	2648.76	0	14603.80
Sunny Days per Annum	1187	212.15	33.93	23	300
Commute Time (Minutes)	1187	20.22	5.38	9	43

6. Statistical Specifications

We estimated Equation 4 using a random effects specification on monthly panels of email networks, revenues and survey data on ESS Use and ESS Skill. We employed random effects to recover parameter estimates of important cross sectional variables (e.g. education, organizational position, industry experience, ESS Use and ESS Skill). We replicated random effects analyses using an OLS specification on annual data in 2002, the year in which the survey was conducted. We then tested relationships between revenues, completed projects, multitasking and project duration using Feasible Generalized Least Squares (FGLS), fixed effects and random effects specifications at the daily level. As daily panel estimates displayed serial correlation based on Durbin-Watson tests and heteroskedasticity based on Breush-Pagan tests, we model FGLS specifications using within-panel corrections for both heteroskedasticity and autocorrelation, with autocorrelation in the error diminishing uniformly over time: $\varepsilon_t = \rho\varepsilon_{t-1} + u_t$. We conducted Hausman tests of the efficiency and consistency of random effects specifications in daily analyses and all tests revealed the random effects specifications to be efficient and consistent. We then examined OLS estimates of the relationships between independent variables and multitasking at the project-level with a variable indexing right censored data, and employed a Maximum Likelihood specification to test the Cox proportional hazards model of project completion rate. We report standard errors according to the White correction (White 1980), and as project analyses may cluster on groups of project team members, we report robust standard errors clustered by project team in project-level analyses.[15] More detail regarding statistical specifications is reported in Appendix D.

7. Results

We first took a more traditional approach and examined the relationship between IT and revenues directly and evaluated a popular conception of how IT may improve productivity – by increasing the pace of work – by estimating the reduced form Equation 4. While we expected these estimates, which ignore the intermediate process steps hypothesized in the production function, to exhibit greater noise, we did indeed find evidence of positive and statistically significant correlations among IT, network position and individual revenues. A one standard deviation increase in betweenness centrality in the email network is associated with approximately $76,000 greater revenue output per year controlling for human capital, demographic variables and use of the ESS system. A one standard deviation increase in network diversity is associated with approximately $83,000 greater annual revenue output (see Model 1, Table 3).

[15] Clustered robust standard errors treat each team as a super-observation for part of its contribution to the variance estimate (e.g. $\varepsilon_{ci} = \eta_c + \upsilon_{ci}$, where η_c is a group effect and υ_{ci} the idiosyncratic error). They are robust to correlations within the observations of each group, but are never fully efficient. They are conservative estimates of standard errors as team members' effort shares vary over projects, such that teams with similar composition expend independently varying levels of effort across projects.

Table 2: Panel Data Descriptive Statistics

	All Employees					Partners					Consultants					Researchers				
Variable	**Obs.**	**Mean**	**SD**	**Min**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Max**	**Obs.**	**Mean**	**SD**	**Min**	**Max**
Monthly Data																				
Age	522	42.36	10.94	24	67	162	50.5	5.70	40	63	216	43.67	9.87	27	67	144	31.25	7.14	24	53
Gender (1=male)	657	.56	.50	0	1	234	.65	.48	0	1	279	.52	.50	0	1	144	.50	.50	0	1
Industry Experience	522	12.52	9.52	1	39	162	21.72	7.85	9	39	216	11.25	7.47	1	30	144	4.06	2.59	1	11
Education	522	17.66	1.33	15	21	162	18.5	1.02	17	21	216	17.29	1.21	15	20	144	17.25	1.39	16	21
Total Emails	563	145.69	110.16	0	592	224	125.52	81.71	1	391	215	119.94	90.10	1	541	124	226.77	143.85	0	592
Sent Emails	563	80.31	59.67	0	342	224	57.20	44.09	0	242	215	57.06	44.70	0	240	124	111.42	71.36	0	253
Received Emails	563	69.09	56.16	0	253	224	71.73	44.84	0	232	215	66.26	49.19	0	306	124	120.15	79.58	0	342
In Degree	563	79.99	70.38	0	445	224	66.90	49.57	0	230	215	61.11	49.71	0	260	124	136.38	98.67	0	445
Out Degree	563	79.99	61.21	0	344	224	70.25	42.05	0	202	215	64.67	49.67	0	308	124	124.14	84.12	1	344
Network Size	563	16.81	8.79	1	58	224	17.92	6.92	1	35	215	14.33	7.05	1	41	124	19.13	12.73	1	58
Betweenness Centrality	563	59.20	73.75	0	895.3	224	55.98	50.08	0	279.85	215	41.58	51.11	0	316.68	124	95.56	117.76	0	895.28
Network Diversity	563	.71	.17	0	.91	224	.75	.14	0	.91	215	.69	.18	0	.89	124	.68	.20	0	.89
ESS Use	531	28.71	20.52	0	75	180	24.45	19.35	0	75	207	28.52	23.03	0	75	144	34.31	16.51	0	65
ESS Skill	531	6.23	1.65	2.52	9.32	171	5.44	1.57	2.52	8.32	216	6.20	1.64	3.27	9.3	144	7.22	1.18	5.64	9.32
Revenues	630	20962	18843	0	80808	234	28462	17121	0	80808	261	22284	17931	0	66934	135	5404	13695	0	55066
Completed Projects	630	.39	.36	0	1.69	234	.49	.32	0	1.69	261	.45	.36	0	1.47	135	.10	.25	0	1.06
Multitasking	630	5.84	5.20	0	24.96	234	8.79	5.10	0	24.96	261	5.38	4.13	0	16.46	135	1.64	3.94	0	16.25
Ave. Project Duration	630	225.23	165.77	0	921.04	234	309.44	146.71	0	921.04	261	235.48	134.13	0	630	135	59.45	127.99	0	438.33
Daily Data																				
Completed Projects	104982	.017	.017	0	.84	44286	.020	.016	0	.839	37537	.020	.018	0	.622	23160	.004	.009	0	.157
Revenues	100815	694.82	690.24	0	3353.35	44286	901.69	664.67	0	3205.53	35564	812.78	689.23	0	3353.35	23066	134.58	358.29	0	2174.67
Multitasking	104983	6.55	5.51	0	28	44286	9.07	5.24	0	28	37537	6.61	4.68	0	22	23160	1.65	3.70	0	17
Share-Weighted Multitasking	104983	3.36	2.91	0	14.25	44286	4.16	2.54	0	14.25	37537	4.02	2.95	0	14.03	23160	.77	1.81	0	8.7
Ave. Project Duration	107658	212.01	158.55	0	1218.75	44775	280.24	143.98	0	1218.75	39724	222.98	129.33	0	630	23160	61.30	127.14	0	618

These results are corroborated by the panel data estimates which show corresponding increases of $3,400 and $1,900 in revenue output per month (see Model 2). A one unit increase in ESS Skill is associated with approximately $26,000 greater annual revenue output and $2,700 greater revenue output in monthly panel data estimates. However, to our surprise, we also found that our IT and information flow variables were not correlated with reductions in project duration, but instead were correlated with *longer* project duration on average (in some specifications these results were even statistically significant). While IT seemed to help individual workers bring more revenue to the firm, it was not simply speeding up their work.

Table 3. Individual Models of Revenue, Multitasking and Project Duration

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Revenue	Revenue	Multitask	Multitask	Duration	Duration
	OLS	RE	OLS	RE	OLS	RE
Betweenness	76,394.91**	3422.42**	1.01	.33	3.79	-8.07
Centrality	(29884.78)	(1454.50)	(.82)	(.327)	(14.20)	(6.39)
Network	83,163.57***	1951.35*	1.64**	.17	-19.71	-13.02**
Diversity	(20823.05)	(1087.45)	(.72)	(.248)	(12.49)	(4.88)
ESS	-1088.54	-82.95	-.013	-.02	.13	-.84
Use	(933.22)	(96.51)	(.03)	(.032)	(.53)	(.81)
ESS	26429.93*	2687.44*	.83*	.16	6.75	6.23
Skill	(14004.34)	(1428.13)	(.46)	(.472)	(7.94)	(12.07)
Partner	309,043.40***	22667.93**	12.54***	3.98	192.21***	-22.50
	(91232)	(9347.66)	(2.39)	(3.03)	(41.53)	(76.90)
Consultant	312,023.70***	13747.44*	13.42***	.54	162.87***	-50.20
	(75178.52)	(7157.21)	(1.84)	(2.314)	(31.95)	(58.56)
Gender	-50786.33	-6305.33	-.70	-1.98	-33.95	5.36
	(44742.07)	(3970.34)	(1.32)	(1.310)	(22.84)	(33.49)
Education	-8322.59	-2452.33	-.34	-.09	3.84	9.26
	(16333.10)	(1702.54)	(.49)	(.560)	(8.47)	(14.28)
Industry	-3746.04	-290.05	-.13	-.02	.12	3.82*
Experience	(2629.76)	(246.35)	(.09)	(.081)	(1.60)	(2.08)
Obs.	42	311	54	311	54	311
Adj R^2	.50	.21	.51	.18	.45	.23
F / χ^2	5.50***	29.89**	7.19***	21.56	5.85***	36.41**

***p<.001; **p<.05; *p<.10. OLS analysis on yearly variables in 2002 (Models 1, 3 & 5); Random Effects estimates on monthly panel data (Models 2, 4 & 6)

Our interviews revealed that employees often vary the number of projects they work on at a time such that workers' revenues are a function not only of how fast they work, but also of how much they multitask. Our estimates of the simple reduced form model provide some support for the association with multitasking (see Model 3). We therefore proceed by estimating the fully specified production functions which estimate intermediate production processes.

7.1. Drivers of Production

We hypothesize that the key driver of output is the number of projects completed per unit time. As recruiters complete projects, they generate revenue for the firm. Our model of the production process therefore hypothesizes that the first intermediate variable in the 'black box' is completed projects, as shown in Figure 1. We tested this hypothesis by examining the relationship between completed projects and revenue generation per person per day over the five year period. The results demonstrate that the number of completed projects per day is strongly correlated with individual revenue generation. The individual worker's share of the revenue generated from a day's work on an eventually completed project is worth, on average $2,149.19 dollars per day for the firm (Table 4, Model 1).

Table 4: Individual Panel Data Estimates of Project Completion and Revenue Generation

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Dependent Variable:	Revenue	Log (Revenue)	Log (Revenue)	Log (Revenue)	Log (Complete Projects)	Log (Complete Projects)	Log (Complete Projects)
Specification	*FGLS*	*FE*	*FE*	*RE*	*FE*	*FE*	*RE*
	Daily	*Daily*	*Daily*	*Daily*	*Daily*	*Daily*	*Daily*
Completed Projects	2149.19*** (43.41)						
Log (Multitasking)		1.024*** (.005)	3.796*** (.037)	3.792*** (.036)	1.202*** (.002)	3.822*** (.013)	3.816*** (.013)
Log (Multitasking Squared)			-1.496*** (.020)	-1.495*** (.019)		-1.416*** (.007)	-1.413*** (.007)
Log (Duration)		-.206*** (.011)	-.153*** (.011)	-.157*** (.011)	-.878*** (.005)	-.835*** (.004)	-.836*** (.004)
nEducation	2.10 (1.62)			.008 (.032)			.007 (.012)
Gender	-.73 (3.72)			.058 (.066)			.029 (.023)
Partner	654.17*** (11.42)			.275** (.114)			-.003 (.040)
Consultant	521.14*** (10.23)			.065 (.104)			-.007 (.037)
Time Controls	Month, Year	Month, Year	Month, Year	Month, Year	Month, Year	Month, Year	Month, Year
Log Likelihood	-370966.8	-	-	-	-	-	-
X^2(d.f) / F(d.f)	8976.9*** (20)	8055.61*** (17)	8746.09*** (18)	157616*** (22)	23506.3*** (17)	40334.4*** (18)	729644*** (22)
Observations	78201	53041	53041	53041	56649	56649	56649

***p<.001; **p<.05; *p<.10. "n"=Normalized Variable; Multitasking terms are effort share weighted.
Hausman Test Results (RE Consistent & Efficient - Models 3 & 4): 16101.23***, p < .001.
Hausman Test Results (RE Consistent & Efficient - Models 6 & 7): 69.80***, p < .001.

We then tested the second fundamental hypothesis of our model: that both revenues and completed projects are closely tied to the number of simultaneous projects an individual works on per unit time (multitasking), and by the average duration of projects. We examined the relationship between multitasking, average duration, revenues and completed projects in Models 2-7 in Table 4. The results demonstrate that more simultaneous projects and faster completion times (shorter duration) are associated with greater project completion and revenue generation per person per day. The multiplicative model in Equation 5 facilitates an intuitive interpretation of the parameter estimates – a 1% increase in multitasking is associated with a 1% average increase in revenues and completions, whereas a 10% increase in average project duration is associated with a 1-2% decrease in revenues and approximately an 8-9% decrease in completions on average. We also find that the relationship between multitasking and output is non-linear. The coefficient on the multitasking squared term is negative and significant implying a concave relationship, such that more multitasking is associated with greater revenue generation and project output to a point, after which there are diminishing marginal returns, then negative returns to increased multitasking. We believe this demonstrates a fundamental tradeoff between workload and efficiency as hypothesized, however we considered three alternate explanations and let the data speak to which is the most likely.

First, correlated differences between individual workers and their project portfolios could produce the inverted-U shaped relationship between multitasking and output. For example, new inexperienced workers may take on fewer less valuable projects, while the most experienced consultants take on the largest number of projects. These two clusters could explain the first and last third of the inverted-U while partners' social and organizational power (e.g. Pfeffer 1981) could enable them to take on a relatively small number of high revenue value projects, creating a relationship between leisure (less multitasking) and revenues in the partner strata of our data. This explanation is consistent with incentive theories of deferred compensation, where workers are underpaid early on in their careers (e.g. [Pay=f(revenues)] < marginal revenue product) and paid more than their marginal revenue product later on (Lazear 1979). Second, there may be unobservable drivers of both multitasking and output that create the inverted-U shaped relationship. For instance, productive workers may spend time on other tasks we don't observe (like networking) that allow them to work on fewer projects simultaneously while producing more output. If these productive workers worked on slightly more projects than inexperienced new workers, but fewer projects than experienced workers who did not spend time on these unobserved tasks, an inverted-U shaped relationship between multitasking and output could be observed. Third, there could be exogenous temporal variation. Clients may hire top management teams in groups, creating temporal clusters of contracts that are both few in number and high in revenue value. If this type of turnover happens seasonally – for example, near the beginning or end of the fiscal year – then temporal clusters of fewer high revenue value projects could create the inverted U-shaped relationship. Exogenous transitory shocks to client demand could also inspire ramping up of production, or large simultaneous layoffs in low revenue value positions.

While the alternate explanations conform to theory and could explain the inverted-U shaped relationship between multitasking and output, our specifications suggest they are unlikely. Our controls for managerial level and industry experience go a long way toward holding constant variation driven by status, organizational power or career tenure, and our estimates of the relationship between multitasking and output are robust to specifications controlling for unobserved heterogeneity across individuals, accounting for aspects of social and organizational power, for unobservable practices (e.g. networking), and for other individual characteristics which could contribute to the shape of the relationship between multitasking and output. Our controls for temporal variation (both seasonal variation and exogenous shocks to demand) also discount explanations based on temporal clusters of projects of different types. As our quantitative and qualitative data discount the alternative explanations, we are drawn to interpret the results in Table 4 as evidence of a fundamental tradeoff between workload and efficiency.[16]

7.2. Relationships between IT, Information Flows and Multitasking

To test whether IT use and skill, and properties of the flow of information in workers' email traffic are related to the intermediate output variables associated with production, we first tested the relationship between our IT and information flow variables and project-level multitasking. Our analysis included controls for team characteristics and job class, but not for city characteristics, which are potentially salient

[16] Since we have not controlled for all possible sources of endogeneity or identified equilibrium values of multitasking and output, the optimal levels of multitasking implied by our parameter estimates may not be precise optima in equilibrium.

for project duration but should not influence how many projects teams work on.[17] The coefficients in Table 5, Models 1 and 3 demonstrate that teams whose members were heavy multitaskers communicated with more people over email and significantly fewer people over the phone. Since the variables have been normalized, they can be interpreted as follows: a one standard deviation increase in the number of email contacts is associated on average with a .30 standard deviation increase in the number of simultaneous projects the team is working on during the focal project (see Model 3).

Table 5: Information Technology Use & Multitasking at the Project-level

Dependent Variable	*Multitasking*		
	Model 1	Model 2	Model 3
	OLS-c	OLS-c	OLS-c
nF2F Contacts	.030 (.036)		.038 (.036)
nPhone Contacts	-.224** (.090)		-.229** (.088)
nEmail Contacts	.320*** (.091)		.305*** (.093)
nESS Skill		.036 (.078)	-.029 (.081)
nESS Use		.114* (.064)	.061 (.061)
Team Size	.227** (.090)	.285** (.110)	.207* (.115)
Education	.102** (.052)	.077 (.055)	.101* (.051)
Industry Experience	-.002 (.007)	.001 (.006)	-.002 (.007)
Constant	-1.98* (1.121)	-1.65 (1.146)	-1.90* (1.114)
Job Class Controls	YES	YES	YES
Time Controls	Year	Year	Year
Censor Dummy	YES	YES	YES
F Value (d.f)	8.49*** (19)	7.90*** (18)	7.88*** (21)
R^2	.16	.12	.16
Obs.	1372	1372	1372

***p<.001; **p<.05; *p<.10. OLS-c = Robust Clustered Standard Errors (n = 505 Clusters)
"n" = Variable normalized by subtracting the mean and dividing by the standard deviation.

Teams who use the ESS system more also work on more projects simultaneously (Model 2).[18] As synchronous technology (i.e. telephone) is associated with lower multitasking while asynchronous technol-

[17] We also ran the same analysis controlling for the revenue value of projects with no qualitative change in the coefficients. The models include a dummy variable for whether the project was right censored during the observation window.

[18] The coefficient on ESS Skill is positive and significant when entered alone, but not when controlling for ESS Use. ESS Use is significant at $p < .001$ in the full model (Model 3) when standard errors are robust but not clustered by project team.

ogy (i.e. email, and to a lesser extent ESS) is associated with greater multitasking, information workers who juggle more projects seek information in ways that do not require coordinated scheduling.

We also tested the analogous relationships between workers' email traffic and their amount of multitasking. The results for both the levels and structure of information flows in teams' email are reported in Table 6, Models 1-6.[19]

Table 6: Information Flows & Multitasking at the Project-level

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent Variable			*Multitasking*			
	OLS-c	OLS-c	OLS-c	OLS-c	OLS-c	OLS-c
Information Flow Level & Network Structure						
nTotal Emails	.321*** (.067)					.266** (.104)
nNetwork Size		.304*** (.068)				
nIn Degree			.301*** (.069)			
nOut Degree				.362*** (.060)		
nBetweenness					.307*** (.060)	.126* (.076)
nNetwork Diversity (1-Constraint)					.134* (.071)	.181** (.089)
Controls						
Team Size	.223*** (.069)	.278*** (.074)	.221** (.071)	.226*** (.068)	.211** (.076)	.211** (.066)
Yrs Education	.090* (.046)	.085 (.052)	.079 (.048)	.091** (.044)	.084* (.049)	.087** (.042)
Industry Experience	.006 (.007)	-.002 (.006)	.006 (.007)	.007 (.006)	.004 (.006)	.003 (.005)
Constant	-2.128** (1.03)	-2.13* (1.09)	-1.870* (1.056)	-2.232** (.995)	-1.795* (1.083)	-.1960** (1.002)
Job Class Controls?	YES	YES	YES	YES	YES	YES
Temporal Controls:	Year	Year	Year	Year	Year	Year
Censor Dummy?	YES	YES	YES	YES	YES	YES
No Email Dummy?	YES	YES	YES	YES	YES	YES
F Value (d.f)	9.33*** (18)	8.35*** (18)	8.94*** (18)	10.41*** (18)	9.56*** (19)	9.62*** (20)
R^2	.20	.18	.19	.23	.20	.24
Observations	1372	1372	1372	1372	1372	1372

***p<.001; **p<.05; *p<.10. OLS-c = Robust Clustered Standard Errors (n = 505 Clusters) "n" = Variable normalized by subtracting the mean and dividing by the standard deviation.

All four measures of communication levels demonstrate strongly that heavy multitaskers communicate more over email. These results strengthen and extend the result from the survey measure of email contacts reported in Table 5.[20] When considering the structural properties of workers' email traffic, more multitasking is associated with greater betweenness centrality – a proxy for the probability of being privy to a given piece of information flowing through the communication network of the firm. Heavy multi-taskers are in the 'thick' of the flow of information and are likely to be 'in between' a larger number of pairs of other employees in terms of their communication structure. Peripheral individuals, with weaker access to information flows, multitask less. Similarly, employees with 'redundant contacts' also multitask less. The negative coefficient on the constraint variable shows that those entangled in closed networks (networks whose members are all closely tied together) work on fewer projects simultaneously. Both the level and the structure of information flows correspond strongly with multitasking behavior and structural parameters remain significant even when controlling for total email volume in Model 6.[21] These results demonstrate a strong correspondence between multitasking and the structure and level of email traffic. However, unobserved characteristics of project assignment may simultaneously drive multitasking and IT use. For example, it could be that multitasking is used more for simpler projects that are more readily accomplished via email. If so we may observe a correlation between multitasking and email use due to the nature of project assignment. To address these concerns, we examined the most likely sources of endogeneity in detail. We found that although simpler, lower revenue projects exhibited more multitasking (Revenue: $\beta = -644$; $t = 2.27$), project revenue was associated with less total email ($\beta = -4288.35$; $t = 2.61$) and with less database use ($\beta = -.112$; $t = 3.36$), discounting the possibility that simpler projects simultaneously drive more multitasking and more email and database use.[22] We also find email and ESS use are associated with greater multitasking when controlling for project type and revenue. Although pro-

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[19] The models include a dummy variable for whether the project was right censored during the observation window. Variables that are highly collinear are entered separately into the regressions.

[20] The parameter estimates from the survey measure are very close to the measure of real email contacts collected from the corporate server (.304 in Table 5, Model 3; .305 in Table 6 Model 2).

[21] It seems intuitive that employees working on more projects at once need to be aware of more lines of communication and information, and thus appear in these structural positions. However, we cannot make causal claims about these results. Heavy multitaskers may seek more information and position themselves in the thick of information flows, or highly central employees may be chosen to conduct more tasks, or may chose to conduct more tasks on their own. Nevertheless, information flows are associated with the multitasking behavior of information workers in our data.

[22] While projects in the medical field exhibit more multitasking, total email use and the number of email contacts is fairly constant across project categories, discounting the hypothesis that project assignment simultaneously drives IT use and multitasking.

ject assignment may be non-random, it does not seem to explain relationships between IT use, email and multitasking.

7.3. Relationships between IT, Information Flows, Multitasking and Project Duration

To test relationships between multitasking, IT, information flows and project duration, we estimated the hazard rate model of project completion rate. Our specification tests the relationship between explanatory variables and projects' instantaneous transition rate – a measure of the likelihood of project completion at time *t*, conditional on the project not having completed before *t*. Table 7 shows analyses of the relationship between IT, multitasking and project completion rate, controlling for *job type*, *task characteristics*, and *city characteristics*.

Table 7: Hazard Rate Analysis of the Impact of IT and Multitasking on Project Completion Rate

Dependent Variable	*Project Completion Rate*		
Variables	**Model 1**	**Model 2**	**Model 3**
	RSE-c	RSE-c	RSE-c
IT Variables			
nFTF Contacts	1.002 (.027)		1.015 (.029)
nPhone Contacts	1.109* (.061)		1.073 (.062)
nEmail Contacts	.974 (.043)		.958 (.046)
nESS Use		1.118*** (.035)	1.114** (.038)
nESS Skill		.947 (.051)	.949 (.060)
Team Controls			
Team Size	.854** (.067)	.820** (.067)	.842** (.071)
Industry Experience	.989** (.004)	.990** (.005)	.991** (.005)
Task Controls			
nRoutineness	1.003 (.042)	1.074* (.043)	1.042 (.047)
nInterdepend.	.980 (.038)	.957 (.034)	.979 (.041)
nMultitasking	.858*** (.030)	.843*** (.029)	.851*** (.030)
Job Class Controls?	YES	YES	YES
City Controls?	YES	YES	YES
Log Likelihood	-7080.3	-7077.6	-7076.03
X^2 (d.f)	185.07*** (19)	193.16*** (18)	196.79*** (21)
Obs.	1180	1180	1180

***p<.001; **p<.05; *p<.10. RSE-c = Robust Clustered SE (n = 505 Clusters)

Multitasking is strongly associated with slower completion rates. Teams with a one standard deviation increase in project-level multitasking (approximately 2.8 additional projects) complete projects about 15% slower on average. These results corroborate our interpretation of the drivers of the inverted-U shaped relationship between multitasking and output. Teams that multitask more take longer to finish projects – a result consistent with a loss of efficiency at high levels of multitasking. Holding the level of multitasking constant, teams using the ESS to gather more information (S.D.= 15%) complete projects on average 11% faster, and teams that use the phone more also execute projects faster. These results are a departure from our simple model of the impact of IT on project duration which did not control for the level of multitasking, indicating the analytical value of our more comprehensive model.[23] These results demonstrate that 1) multitasking is associated with longer project duration on average, and 2) IT use is associated with increases in output at all levels of multitasking, perhaps by enabling greater workloads without corresponding losses of efficiency.[24] We also analyzed how information flows and multitasking correspond to project completion rates.[25] All control variables and the multitasking variable display significant results of almost identical magnitude as reported in Table 7. However, none of the six network variables returned a significant parameter estimate.[26] While the levels and structure of information flows predict multitasking, they do not predict the speed with which projects are completed, controlling for multitasking. Although ESS use is associated with 11% faster project completion, comfort with and ability to use these tools decline with age (Spearman's ρ=-.47, p<.001, Spearman's ρ=-.31, p<.02), suggesting that targeted training in ESS use could speed project completion at the firm. Overall, as multitasking is associ-

[23] Team size and industry experience are associated with longer project duration and slower completion rates. Teams with more members may take longer to execute projects due to the added complexity of coordination, or the firm may resort to 'throwing more labor at' difficult jobs or jobs that are taking longer to complete than expected. Controlling for team size therefore may also account for differences in project difficulty not picked up by controls for job type, task, and city characteristics. Industry experience also corresponds to longer project duration perhaps because less experienced employees receive less demanding work. Cost of living, crime rates, and greater commute times all reduce the project completion rate on average, meaning these characteristics may be less attractive to potential candidates, while good weather is associated with increased completion rate. Routine tasks consistently finish faster, and greater interdependence among team members is associated with slower completion rates.

[24] We found no convincing evidence of any interaction effect of multitasking and IT use on the project completion rate in separate analyses, indicating that IT use enables greater project completion per unit time at all levels of multitasking.

[25] Detailed results on "Hazard Rate Analysis of the Impact of Information Flows and Multitasking on Project Completion Rate" are omitted due to space constraints, but are available upon request from the authors.

ated with slower project completion rates, productive information workers trade longer task duration per project for more tasks per unit time by working on multiple projects in parallel, and use asynchronous information and communication technologies to offset multitasking delay costs.

8. Discussion and Conclusion

To date, most important advances in assessing IT business value were achieved through the use of more sophisticated econometric methods or more comprehensive firm-level and plant-level data. In contrast, our research seeks to open two new frontiers: (1) objective measures of information flows through social networks, and (2) detailed task-level evidence of information worker output. This approach provides a higher resolution microscope with which to study organizational phenomena, revealing finer grained relationships than would be possible with any amount of firm, industry, or country-level data.

Three contributions result from this approach. First, we show that information work can, in fact, be measured with great precision. We identified a context with objective performance metrics, built tools to directly observe behaviors and information flows in email, and gathered independent data on project quality controls. Our analyses of these data produce precise estimates of the productivity of information workers and reveal underlying production and interaction relationships. While information work has often defied measurement in the past, we found it remarkably quantifiable in this setting.

Second, when we apply social network analysis to our email data, we find that position and flow are critically important. Recruiters with diverse social networks and high betweenness centrality generate more revenue than their peers. Betweenness centrality and network diversity also show positive associations with ability to multitask, as do in-degree, out-degree, and network size. Among information workers, it pays to be a communications broker. Peripheral employees outside the communication flow work on fewer projects per unit time. The total volume of communication is also statistically significant as is network constraint, demonstrating that constrained networks and redundant contacts correspond to less multitasking. An implication of these results for managers is that untangling social networks through stra-

[26] When we remove city controls, network variables predict faster project completions (total email $\beta = 1.051$; $p < .10$, network size $\beta = 1.068$; $p < .05$, in-degree $\beta = 1.055$; $p < .10$, out-degree $\beta = 1.061$; $p < .10$), suggesting interdependence between geo-

tegic job rotation could lead to more efficient multitasking. We also find that richer information flows alone do not necessarily increase the speed with which individuals complete projects. Central information brokers boost their productivity by multitasking more effectively rather than by working faster.

Finally, we build and validate multitasking and hazard rate models of project completions at both individual and team levels. These models highlight intermediate production processes and directly explore the association between using technology, juggling more tasks, and the ability to complete tasks faster. We find that individual differences in IT use behaviors correspond with differences in performance. On average, workers using more asynchronous email and database tools handle substantially more projects simultaneously. In contrast, traditional synchronous communication modes such as phone calls correlate with less multitasking. Further, there were speed implications. People who multitasked heavily benefited from also using the ESS heavily to speed their work, enabling them to complete more projects per unit time, although the benefits of multitasking decreased after a point. These results, together with the survey data, imply that targeted ESS training could improve speed and thus firm performance.

In sum, we find substantial correspondence among information, technology, and output in this setting. It is not just having IT but how one uses it that predicts differences in performance. In particular, our approach demonstrates how email flows reveal how social network structures affect business performance. Tools and techniques developed during this research can be readily applied to other project-level information work involving email and databases including sales, consulting, law, medicine, software development, banking, insurance, and architecture, among others. This portends a substantial improvement in our understanding of the relationships among information flows, technology, and value creation.

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graphic distribution and social network attributes – a result we intend to explore in future research.

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